



New heuristic techniques for general mixed-integer programs

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(Mixed) Integer Programming (IP)

$$\text{Min } c^T x$$

$$\text{Subject to: } Ax = b$$

$$\ell \leq x \leq u$$

$$x = (x_I, x_C)$$

$$x_I \in \mathbb{Z}^n \text{ (integer values)}$$

$$x_C \in \mathbb{Q}^n \text{ (rational values)}$$

- Can also have inequalities in either direction (slack variables):

$$a_i^T x \leq b_i \Rightarrow a_i^T x + s_i = b_i, s_i \geq 0$$

- IP (easily) expresses any NP-complete problem



Linear programming (LP) relaxation of an IP

Min $c^T x$

Subject to:

$$Ax = b$$

$$\ell \leq x \leq u$$

$$x = (x_I, x_C)$$

$$\cancel{x_I} \in \mathbb{Z}^n \text{ (integer values)}$$

$$x_C \in \mathbb{Q}^n \text{ (rational values)}$$

- LP can be solved efficiently (in theory and practice)
- LP optimal gives lower bound



DOE/Science MIP Applications (Small Sample)

Defense program applications:

- Logistics
 - Capacity planning, scheduling, workforce planning, constrained vehicle routing, fleet planning
- Site security
- Tools for high-performance computing (scheduling, node allocation, domain decomposition, meshing)

Science

- Bioinformatics: protein structure prediction/comparison
- Wireless sensor management
- New applications (with Ali Pinar, LBNL)
 - Scheduling telescope time (eg. For supernovae observations)
 - Groundwater monitoring
 - Analysis of particle behaviors in supercolliders



Simple Example: Scheduling telescope

- A number of projects are sharing a telescope
 - Looking for different types of objects
 - Sky regions observed multiple times
 - Quality of a pair of observations depends on time gap
- $x_{ij} = 1$ if observe region i on night j
- $Z_{ijkp} = 1$ if project p uses an observation of region i on nights j and k
- $V_{gp} =$ value to project p for observing with a gap of g
- $n = \#$ of observations/night
- $V_p =$ minimum value for project p



Simple example: Scheduling telescope

$$\max \sum_{ijkp} v_{k-j,p} z_{ijkp}$$

st

$$\sum_{ij} x_{ij} \leq n \quad \text{maximum observations/night}$$

$$z_{ikjp} \leq x_{ik} \quad \forall i, k, j, p$$

$$z_{ikjp} \leq x_{jk} \quad \forall i, k, j, p$$

$$\sum_{ijk} v_{k-j,p} z_{ijkp} \geq V_p \quad \forall p \quad \text{mimum quality}$$

$$\sum_{(i,j,k) \in F} z_{ijkp} \leq 1 \quad \forall p, \text{ overlap sets } F \text{ (no overlapping intervals)}$$



Solution Options for Integer Programming

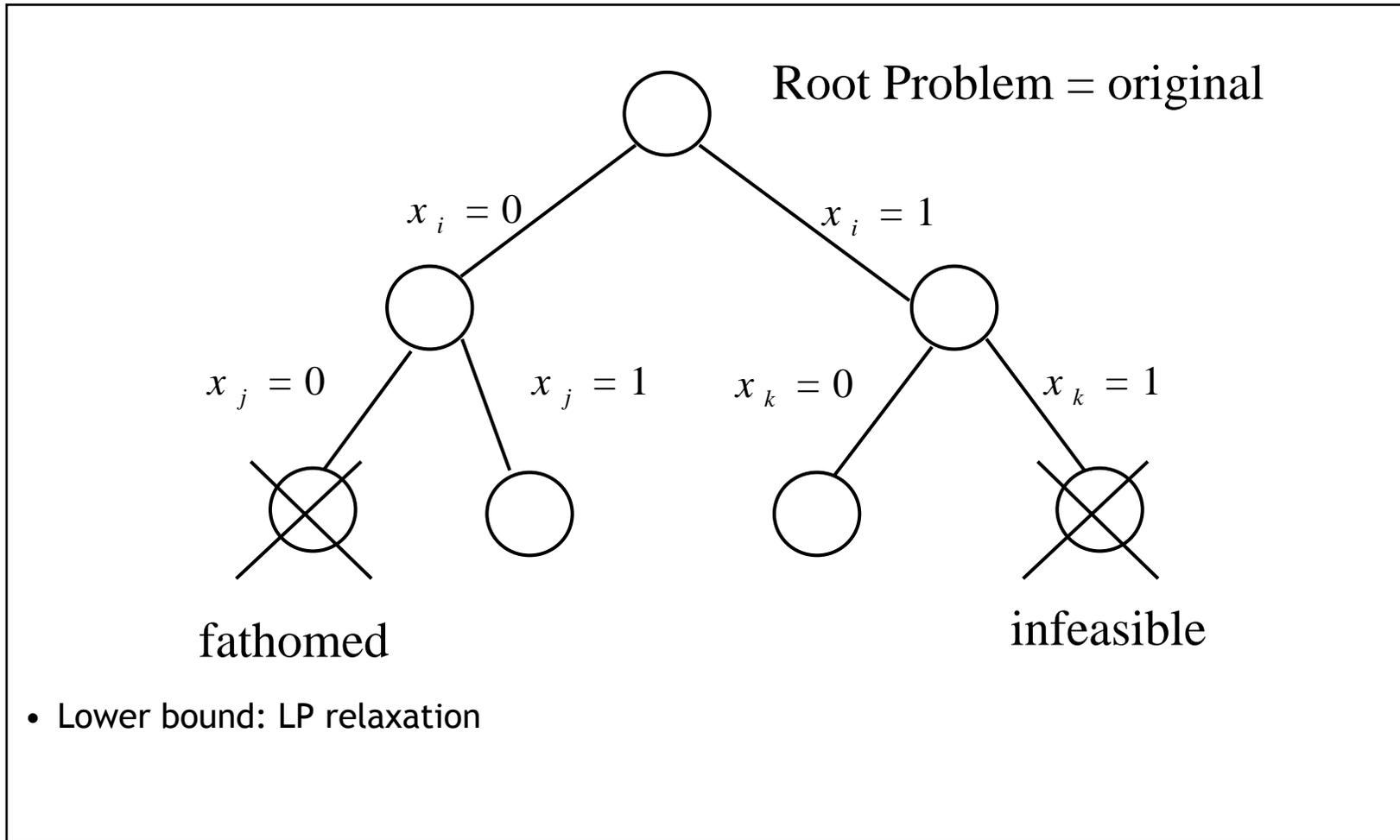
- Commercial codes (ILOG's cplex)
 - Good and getting better
 - Expensive
 - Serial (or modest SMP)
- Free serial codes (ABACUS, MINTO, BCP)
- Modest-level parallel codes (Symphony)
- Grid parallelism (FATCOP)
- In development: ALPS/BiCePs/BLIS

- Massive parallelism: PICO (Parallel Integer and Combinatorial Optimizer)

Note: Parallel B&B for simple bounding: PUBB, BoB/BOB++, PPBB-lib, Mallba, Zram



Solving Integer Programs: Branch and Bound



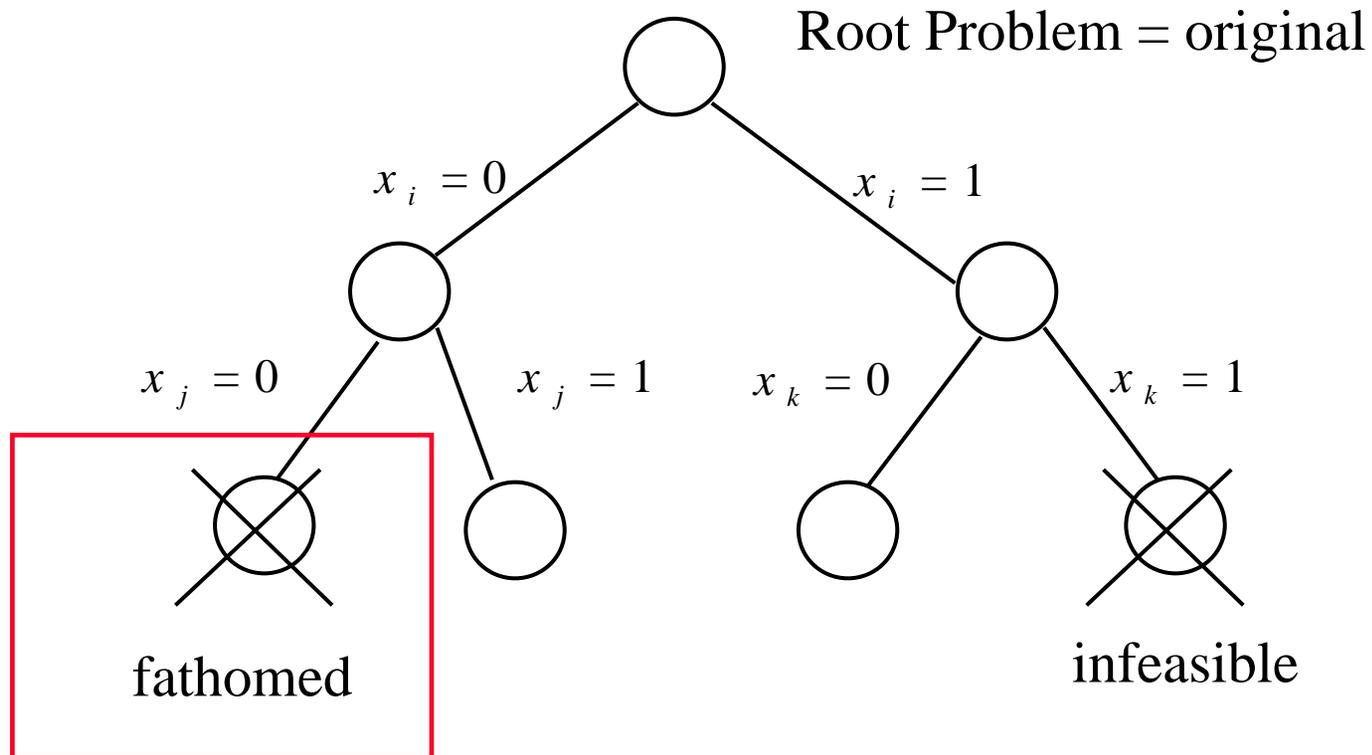


PICO Parallel IP Solver: Two Phases

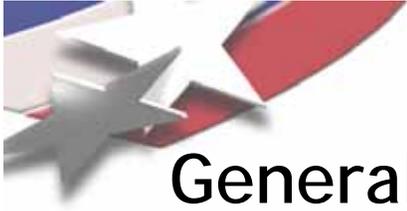
- Parallel subproblem phase
 - There are plenty of subproblems compared to # processors
- Ramp up (eg. 1 subproblem, 10000 processors)
 - Parallel processing of single problem
 - Gradients
 - Cuts
 - LP bounds
 - **Incumbent heuristics** (looking for a good feasible solution)



Value of a Good Feasible Solution Found Early



- Faster pruning
- Having something to say if the computation stops early



General-Purpose Incumbent Heuristics

- Randomized rounding
- Feasibility pump
- Nediak-Eckstein
- Fractional Decomposition Tree



Randomized Rounding

Binary decision variables. LP relaxation x^*

- Simplest form: treat LP relaxation $0 \leq x^* \leq 1$ probability
- Select each x^* independently with probability x^*
- For parallel IP, in early computation, many processors can do this independently.
- Resulting vector x is
 - Integer by construction
 - Almost certainly infeasible for linear constraints $Ax = b$.
 - Exception: covering problems [Raghavan, Thompson]
- Fast way to find something when (almost) everything is feasible



Feasibility Pump (Fischetti, Glover, Lodi)

Basic algorithm:

1. Solve LP to obtain x^*
2. Round (arithmetically) x^* to \tilde{x}
3. While \tilde{x} is not feasible obtain new x^* from this LP:

$$\begin{aligned} \min \quad & \sum_i y_i \\ \text{s.t.} \quad & \\ & y_i \geq x_i - \tilde{x}_i \\ & y_i \geq \tilde{x}_i - x_i \\ & Ax = b \end{aligned}$$

and round x to \tilde{x} again



Feasibility Pump Improvements

- Gap is $\frac{\text{value of first feasible solution}}{\text{optimal (or best known)}}$
- Improvement is relative to initial feasibility pump
- Tested with problems from miplib2003
- Round x^* multiple times, take best (most feasible) of k trials
 - 23.7% gap improvement for $k = 30$
 - Running time increase factor of k , but fully parallelizable
- Iterated local search: perturb and redo the feasibility pump
 - For $k=30$ iterations, gap improvement of 31.2%
 - Runtime increase of k , not parallelizable individually, but can do multiple independent iterated searches.
- Good idea to round randomly for x^* components near .5



Eckstein-Nediak Heuristic

- Parallelizable, General 0-1 MIPs

Uses a merit function $\psi(x)$

- motivated by Løkkentangen and Glover, 1998
- $\psi(x) = 0$ if vector x is integer feasible
- $\psi(x) > 0$ if an integer variable is fractional
- $\psi(x)$ is differentiable and strictly concave
 - Important properties, not enforced by Løkkentangen and Glover

Goals:

- Reduce $\psi(x)$ to 0
- Obey linear constraints ($Ax \leq b$) and variable bounds
- Minimize increase in MIP objective ($c^T x$)



Parallel MIP Heuristic Merit Function

We define a separate merit function $\phi_j(x_j)$ for each binary variable x_j

Same properties:

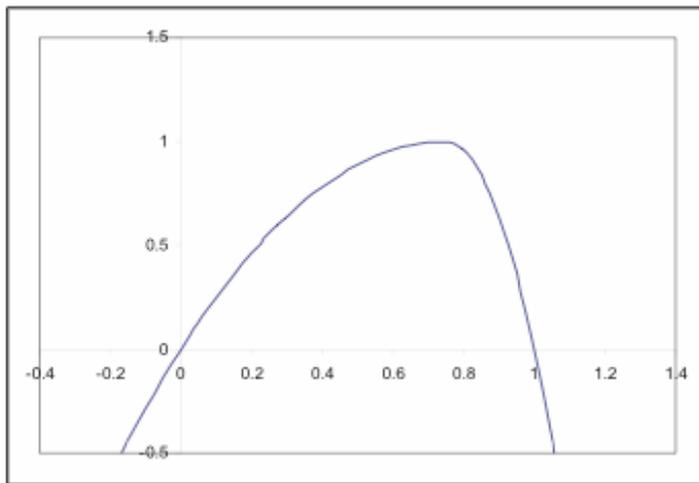
- $\phi_j(0) = \phi_j(1) = 0$
- $\phi_j(x) > 0$ for $0 < x < 1$
- Differentiable, strictly convex

Total merit is the sum of the individual merits (retains properties)

$$\psi(x) = \sum_{j \in I} \phi_j(x_j)$$



Merit Function for a variable x_j



C^1 quadratic spline defined by

- $\phi(0) = 0$
- $\phi(\alpha) = 1$
- $\phi'(\alpha) = 0$
- $\phi(1) = 0$

$\alpha = 0.75$ shown

Specifically, for

$$\alpha \in (0,1)$$

$$\phi_\alpha(x) = 1 - \begin{cases} \left(\frac{x-\alpha}{\alpha}\right)^2 & \text{for } x \leq \alpha \\ \left(\frac{x-\alpha}{1-\alpha}\right)^2 & \text{for } x > \alpha \end{cases}$$



Nediak-Eckstein MIP heuristic

New objective function $\nabla\psi(x^*) + wC$, where

- x^* is the current point (such as LP optimal)
- C is the original IP objective function
- w is a weighting factor (IP objective vs. integrality)

This is the Sum/Frank-Wolfe approach

Use normal LP simplex pivots to improve the new objective

- Adjust the objective at each step (for new x^*)
- Provably finds a local optimum (via concavity)

If the local optimum x has $\psi(x) > 0$, can add Gomory cuts and continue.



Nediak-Eckstein MIP Heuristic

- Processors can use different merit functions
 - Random values of α for each variable
- Processors can also fix one fractional variable
 - For example, if binary variable x_j is .4. Set to 0 or 1 in heuristic.
- Combinations of the two types of variation
 - Fixing variables that have a good history of improving integrality



LP-Relaxation-Based Approximation for IP

- Compute LP relaxation (lower bound).
- Common technique:
 - Use structural information from LP solution to find feasible IP solution (use parallelism if possible)
 - Bound quality using LP bound
- Integrality gap = $\max_I (IP(I)) / (LP(I))$
 - Taken over all instances I (settings of class parameters: c, b)
 - Integrality gap is unbounded (infinite) if
 - $LP(I) = 0$ or
 - IP is infeasible when LP isn't
- This technique cannot prove anything better than integrality gap



Finding an Approximate solution: Convex Decomposition

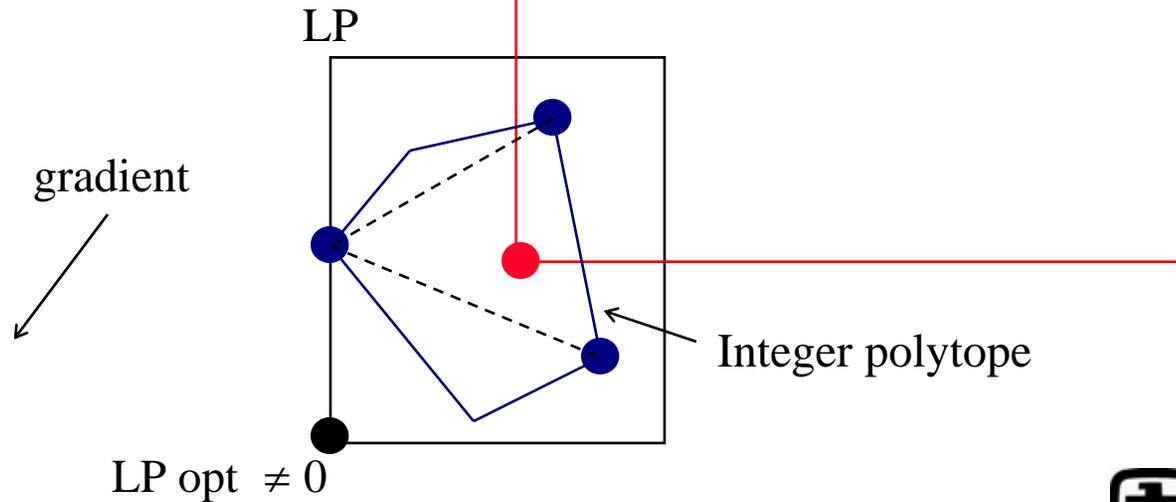
x^* = feasible solution to the LP with cutting planes

Find feasible *integer* solutions

$$S_0, S_1, \dots, S_m \text{ such that } \sum \lambda_i S_i \leq \rho x^*$$

Convex combination: $0 \leq \lambda_i \leq 1$; $\sum \lambda_i = 1$

- Implies one of the S_i has cost at most ρ times the LP optimal





Key Theorem (Carr, Vempala)

- Recall integrality gap = $\frac{\text{value of best integer solution}}{\text{value of LP relaxation}}$
- Let x^* be the optimal LP solution to the LP relaxation for an IP.
There exists a convex decomposition dominated by ρx^* if and only if the integrality gap is ρ for finite ρ .

$$S_0, S_1, \dots, S_m \text{ such that } \sum \lambda_i S_i \leq \rho x^*$$

$$0 \leq \lambda_i \leq 1; \sum_i \lambda_i = 1$$

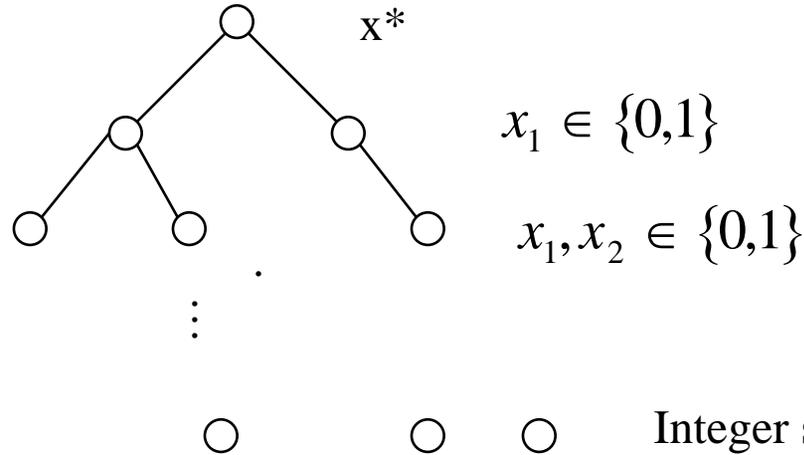


Fractional Decomposition Tree - Overview

- Previous decomposition results were problem-specific
The FDT method applies decomposition to any integer program.
- Will succeed if the problem class has finite integrality gap!
 - Success = find feasible solution
 - No quality guarantee
- Grows a tree-like branch and bound (B&B) except
 - Preserves structure of LP relaxation (vs. preserving objective function in B&B)
 - Limits the tree to polynomial size (vs. exponential for B&B)



FDTs for 0-1 IPs



- Order the variables that are fractional in the LP optimal x^*
- At each level of the tree, one more variable is forced integral
- Use LP to pack the children into the parent optimally
 - Preserve structure of the solution



LP to create the children

- To create children of the root from x^* (LPC):
$$\begin{aligned} \max \quad & \lambda_0 + \lambda_1 \\ \text{st} \quad & Ay^0 \geq b\lambda_0 \\ & Ay^1 \geq b\lambda_1 \\ & 0 \leq y^0 \leq \lambda_0 \bullet 1 \\ & 0 \leq y^1 \leq \lambda_1 \bullet 1 \\ & y_1^0 = 0; y_1^1 = \lambda_1 \\ & y^0 + y^1 \leq x^* \\ & \lambda_0, \lambda_1 \geq 0 \end{aligned}$$
- Children of the root have solutions:
$$x^{0*} = \frac{y^0}{\lambda_0} \quad \text{and} \quad x^{1*} = \frac{y^1}{\lambda_1}$$
- Solutions are feasible, have first variable integral, and decompose x^* with value
$$\rho = \frac{1}{\lambda_0 + \lambda_1} .$$



LPC is feasible in general

- For finite integrality gap, there exists

$$S_0, S_1, \dots, S_m \text{ such that } \sum \lambda_i S_i \leq \rho x^*$$

- Let $S_i^{(1)}$ be the members of S_i with $x_1=1$
 $S_i^{(0)}$ be the members of S_i with $x_1=0$

$$\sum \lambda_i S_i^{(1)} \leq \rho x^*$$

$$\sum \lambda_j S_j^{(0)} \leq \rho x^*$$



Pruning the tree

- Let n be the number of fractional variables in x^*
- If any level of the tree has more than n nodes, we prune the tree, keeping only the best n partially integral solutions.
- This LP (LPP) picks the n survivors that best pack into the root solution x^* and calculates the convex combination parameters.

$$\begin{aligned} \max \quad & \sum_i \lambda^i \\ \text{st} \quad & \sum_i \lambda^i x^i \leq x^* \\ & 0 \leq \lambda^i \leq 1 \end{aligned}$$

- Has only n nonzeros because there are only n constraints



FDT heuristic

- Some of the decompositions will have only one child.
- If any of the x^i are integral, no further decomposition. They can participate in LPP (travel to next “level” logically).
- If this were to run n levels, all leaves would be feasible integral solutions.
- Running to the end level could be very expensive
 - Combine this with randomized rounding or other heuristics



Parallelizing FDT

- Child decompositions on each level are independent
- Alternatively, can “dive” through the FDT
 - Do a child decomposition
 - Pick a single child
 - Travel a single path to a leaf
 - This can fail even when the full computation would not
- Each processor can dive independently



Final remarks

- For important applications, customization is best
 - PICO provides tools for each addition of custom incumbent heuristics
 - If using ampl modeling language, ampl variables are available directly within PICO
- Expect FDT will be the sledgehammer for when nothing else works.
- Key challenge: managing parallel heuristics